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Can User Feedback Help Issue Detection? An Empirical Study on a One-billion-user Online Service System

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User Feedback and Issue Detection

- **User feedback** in large-scale online service systems
  - Describe user experience with the systems
  - An important data resource for service maintenance (e.g., issue detection)

- Challenges of user feedback for issue detection
  - User feedback is abundant but noisy
  - Hard to identify severe issues automatically

How user feedback help issue detection?

Research Questions

- **RQ1:** What **proportion** of feedback actually reports issues?

- **RQ2:** Does **feedback amount** indicate issue severity?

- **RQ3:** Can **certain features** (*e.g.*, sentiment, text length, historical behaviors) of a feedback item indicate issue severity?

- **RQ4:** Are **feedback topics** stable over time?

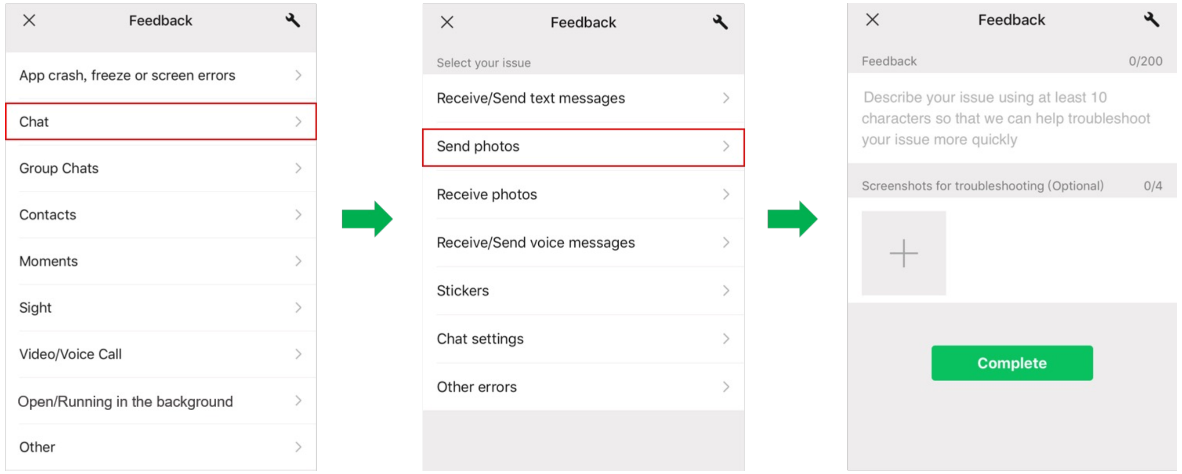
Target System and Dataset

- Target service system: **WeChat**
  - A popular social media platform serving over one billion users
  - Contains diverse online services (e.g., chat, work, entertainment)

- User feedback dataset
  - Six online services from WeChat ecosystem
  - All feedback collected within one year (a total of 50,378,766 items)

TABLE I
SIX SERVICES OF OUR TARGET SOCIAL MEDIA PLATFORM.

Service	Functionality	User Scale
WeChat	Instant Messaging	10^9
WeChat-Work	Workplace Communication	10^8
WeChat-info	Content Subscription	10^8
WeChat-Pay	Mobile Payment	10^8
WeChat-Game	Mobile Game	10^8
WeChat-Reading	Reading	10^8



RQ1: Proportion of Issue-relevant Feedback

- Step 1: Manual analysis
  - Randomly select 10,000 feedback items for manual analysis
  - A large amount (4,450) is *irrelevant* to system issues
- Step 2: Model training
  - Train a **binary classifier** using a labeled dataset of the 10,000 feedback items
    - BERT + TextCNN (F1 = 88.71%)
- Step 3: Prediction for the entire feedback dataset

TABLE II
TOTAL AMOUNT OF FEEDBACK ITEMS AND ISSUE-RELEVANT FEEDBACK ITEMS COLLECTED FROM SIX SERVICES IN ONE YEAR.

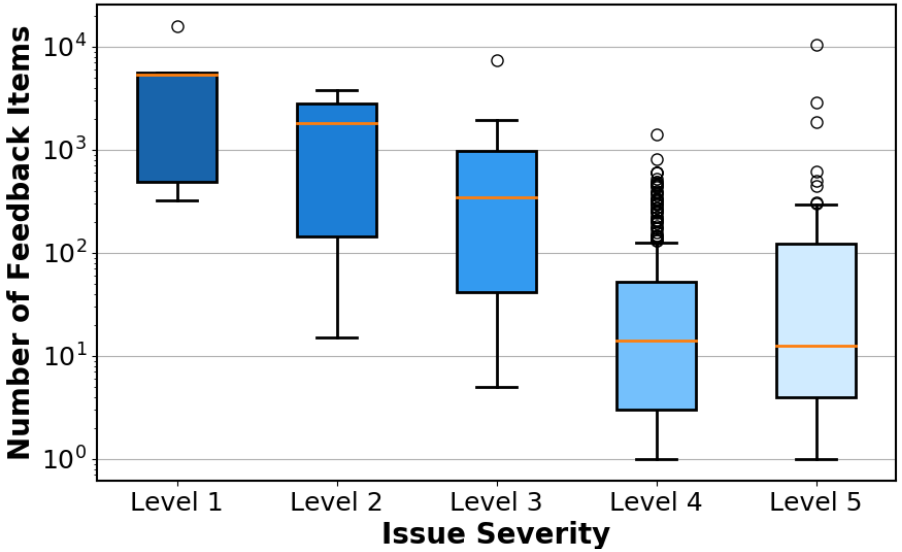
Service	**# Feedback**	**# Issue-relevant**	**Percentage**
WeChat	16,405,550	10,916,729	66.54%
WeChat-Work	20,406,139	2,232,664	10.94%
WeChat-Info	7,771,103	1,289,212	16.59%
WeChat-Pay	2,306,460	652,204	28.28%
WeChat-Game	2,897,146	1,752,791	60.50%
WeChat-Reading	592,368	174,179	29.40%

Answer to RQ1: Only 10.94% ~ 66.54% of user feedback was issue-relevant, revealing the necessity of automated filtering to remove noise.

RQ2: Feedback Amount vs. Issue Severity

- Does more feedback mean more severe issues?

- Analysis from the **issue-tracking system**
  - An **issue ticket** describes a known issue with its *severity level* (1~5, 1 is the most severe)
  - We analyzed all 509 issue tickets in one year and their related user feedback



Answer to RQ2: While severe issues generally attract more feedback, some critical issues were reported by a few users, limiting reliance on volume-based prioritization.

RQ3: Feedback Features vs. Issue Severity

Feature 1: **Sentiment**

Negative sentiment → ? → Severe issues

- Step 1: Sentiment analysis
  - Calculate a **sentiment score** for each feedback text
  - Groups: Negative / Neutral / Positive
- Step 2: Significance test (Z-test)
  - Is feedback in the **negative group** more likely to indicate severe issues?
    - If Z>1.65, yes

TABLE IV
PROPORTIONS OF FEEDBACK ITEMS INDICATING SEVERE ISSUES IN DIFFERENT SENTIMENT GROUPS AND THE Z-TEST RESULTS.

Service	**Sentiment**			**Z value**	
	Neg.	Neu.	Pos.	Neg.-Neu.	Neg.-Pos.
WeChat	24.2%	22.5%	19.6%	0.432	1.215
WeChat-Work	31.7%	24.6%	32.5%	1.308	-0.196
WeChat-Info	24.2%	20.8%	28.3%	0.874	-1.037
WeChat-Pay	19.6%	12.5%	14.7%	**2.114**	1.388
WeChat-Game	39.2%	28.8%	17.5%	**2.410**	**5.267**
WeChat-Reading	25.8%	23.3%	20.0%	0.636	1.520

* Neg.: Negative group, Neu.: Neutral group, Pos.: Positive group

The sentiment of feedback has no significant correlation with issue severity.

RQ3: Feedback Features vs. Issue Severity

Feature 2: **Text Length**

Long feedback texts → ? → Severe issues

- Step 1: Text length analysis
  - Count **the number of characters** for each feedback text
  - Groups: Short / Medium / Long
- Step 2: Significance test (Z-test)
  - Is feedback in the **long-text group** more likely to indicate severe issues?

TABLE V
PROPORTIONS OF FEEDBACK ITEMS INDICATING SEVERE ISSUES IN DIFFERENT TEXT-LENGTH GROUPS AND THE Z-TEST RESULTS.

Service	**Text-length**			**Z value**	
	S.	M.	L.	L.-M.	L.-S.
WeChat	20.6%	24.0%	26.8%	0.615	1.611
WeChat-Work	25.2%	45.1%	37.1%	-1.388	**2.755**
WeChat-Info	22.8%	27.8%	28.8%	0.083	1.319
WeChat-Pay	13.0%	25.0%	18.9%	-1.207	**1.727**
WeChat-Game	29.4%	25.8%	31.4%	1.155	0.462
WeChat-Reading	21.3%	21.5%	27.5%	1.376	1.543

* S.: Short-text group, M.: Medium-text group, L.: Long-text group

The text length of feedback has no significant correlation with issue severity.

RQ3: Feedback Features vs. Issue Severity

Feature 3: **User Historical Behaviors**

Users who reported severe issues before → ? → Report severe issues again

- Historical behavior analysis
  - Among 159 users who reported severe issues, 80 users have submitted multiple feedback
  - 9 users have reported multiple severe issues, averaging 3 issues per user

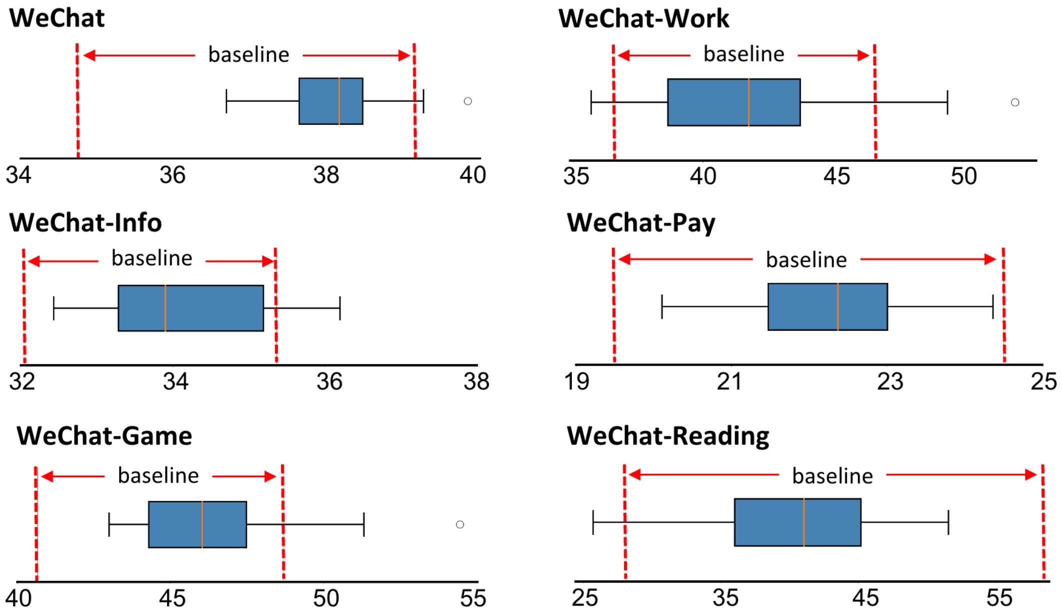
User historical behaviors can indicate issue severity to some extent.

Answer to RQ3: Text-based features (sentiment, text length) showed negligible correlation with issue severity, but historical user behavior (e.g., prior severe-issue reports) can offer some predictive value.

RQ4: Feedback Topic Stability Over Time

- Existing feedback analysis relies on **machine learning** methods
  - The stability of feedback topics affects the performance of AI-based analysis

- Feedback topic similarity analysis
  - Collect issue-relevant feedback from 8 service versions
  - Vectorize feedback texts
  - Measure the *Wasserstein Distance* between versions

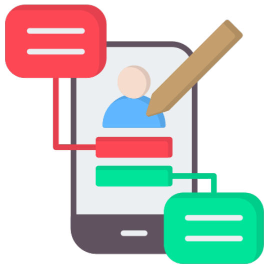


Answer to RQ4: Feedback topic distributions remained stable across service versions and time intervals, validating the feasibility of machine learning for longitudinal analysis.

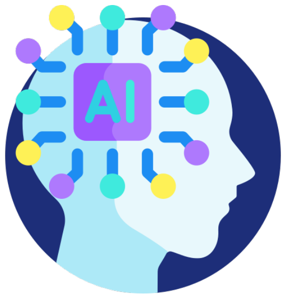
Summary of Key Findings

- High noise in feedback → Filtering needed
- Amount ≠ severity → Need for better prioritization
- Text features are poor predictors → Explore user behavior
- Topics are stable → AI-based analysis is feasible

Implications for Practice



- Improve **feedback interface** design
  - e.g., guided categorization



- Use **AI techniques** for filtering and classification
  - Apply LLMs for large-scale feedback learning
- Combine feedback with **system KPIs**
  - Multiple data sources for better issue detection

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Pre-print

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Thank you!

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